Printing Quality Control Using Template Independent NeuroFuzzy Defect Classification

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Abstract

This paper describes the application of NeuroFuzzy techniques to obtain a template-independent direct method for the identification of printing defects based on parts of 2D-images of the print. This approach is compared with the frequently used 1D scanning approach. It is shown that while these approaches are comparable, the NeuroFuzzy approach requires significant less development time, and has more attractive learning capabilities.

KEYWORDS: computer vision, padprinting, neurofuzzy, mechatronics, image analysis, print quality.

1. Introduction

For outsiders, the first and most striking impression created by machine vision is its weak performance in comparison with human achievement. Humans are visual experts equipped with excellent physiological sensors and a complex, hitherto not fully understood cognitive apparatus to process this information. For instance, humans readily acquire the skills required to identify and classify slight variations and deviations of a given image, and easily outperform current computer vision algorithms.

Human vision is understood as an active, dynamic and parallel process. Images are processed in parallel as complexes of characteristic features, the ‘gestalts’. A ‘focus of attention’ directs feature search for specific clues based on current beliefs. The results of this search generate new beliefs, creating a process that quickly converges to a result: the interpretation of the image.

On the other hand, most computer vision algorithms engage a series of distinct techniques like template matching, optimisation, feature extraction, wavelet or Fourier analysis, and correlation functions. Information is processed sequentially as a fixed input-output system, for normally there are no interactions or feedback loops between the output and the input. This combination yields static, complex to maintain and develop systems, which cannot compete with human vision.

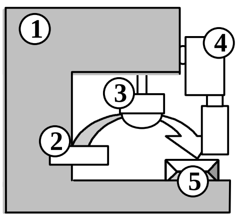

Fig. 1. Schematic drawing of: 1: padprinting machine; 2: cliché, 3: pad, 4: CCD-camera with lighting, and 5: object to be decorated

In this paper we will present results from a research of the application of computer vision to padprinting. Padprinting is a technique that is currently the most efficient and reliable technique for high-yield/low cost printing on curved areas, and one of the most used techniques for decoration on a large variety of commodities. The technique was invented 40 years ago in Southern Germany for the decoration of the faces of clocks. Padprinting uses a cliché with an etched negative of the template for the decoration. The cliché is filled with ink and a silicon rubber pad is pressed on the cliché, from which the ink is transferred with great accuracy to the pad. Subsequently, the pad is pressed on the object, which thereby is decorated. This process is mechanised and automatically controlled to a high perfection. However, due to physical-chemical reasons some defects may occur within the assumed ‘safe’ process settings. Tenths of such defects are known and catalogued. Such defects can always be characterised by their visual effects on the print. For this reason the application of Computer Vision appeared to be a sensible improvement of the process. This led to the development of a control system consisting of three major parts; 1. a Computer Vision system, 2. a system that combines information from a number of sensors with the Computer Vision output, and evaluates the current system state, and 3. an interface to the mechatronics control.

The computer vision system itself consists of :

a. a CCD-camera mounted on the padprinting machine equipped with framegrabber and template-matching hardware and software.
b. a set of algorithms that could automatically generate a hypothesis on the defect of the image, called the LCA-algorithm.
c. a reasoning system that automatically generates hypotheses and new experiments using the LCA-algorithm, and gradually converges to a final conclusion.

Parts b and c were implemented as the ‘LCA-Diag’ algorithm [5]. The performance of the LCA-Diag system in the sense of machine vision was reasonable to good, but padprinting experts were often surprised that defects that were clearly ‘visible’ to them were so difficult and time-consuming to identify by the system. Inspired by the high human performance the authors investigated the performance of a simple feed-forward backpropagation network on this task.

2. 1D Scanprofile Approaches

A much-employed method for analysing 2D-images is scanning analysis. In this method relevant areas of the image of a defect are covered with curves called scans. Next, for each scan the observed intensity profile (the scan profile) is compared with the scan profile of the same curve on the template, see figure 2. Applied to padprinting, the differences between these two profiles depend on the topology of the curve, the relative position on the template (see figure 3), and the printing defect class. Since the first two entities are known, an analysis of the profiles yields information on the printing defect class. Based on statistical analysis of a large number of scan profiles with known printing defects a correlation matrix can be calculated. This matrix can in its turn be used for given scans to compute a probability distribution over the printing defects. Combined analysis of a number of different scans and the correct combination of the corresponding probability distributions eventually leads to an aggregated probability distribution that normally converges to one most likely hypothesis. As on the one hand the topology ‘τ’ of the curve and the relative position ‘π’ on the template can be freely chosen, and on the other hand some combinations of (τ,π) will produce more information on specific defect classes than others, given the current probability-distribution, optimal choices of (τ,π) can be defined.

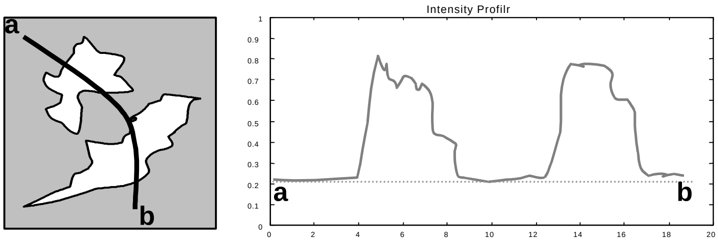

Fig. 2. Left: A print with defect ‘ink missing’. A scan is performed over a curve from point ‘a’ to point ‘b’. Right the intensity over curve *ab* as function of the position on curve *ab*. The expected intensity-profile, i.e. in case no defect had occurred, is indicated as a dotted line.

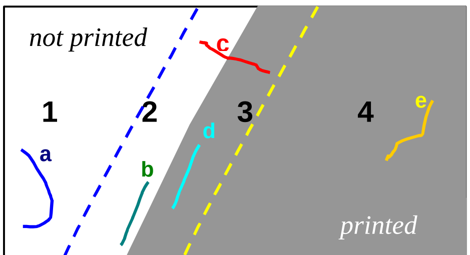

Fig. 3. Typology of positions and curves, depending on *in* or *out*, or *far* or *near* the printed area, or similarly *parallel* or *perpendicular* to the print-border.

The scanning analysis approach described above was implemented with conventional techniques [5]. The performance on a large testset was between 85% and 90%, which is reasonable for this kind of application. However, the scanprofile approach has a number of important disadvantages. First, the approach is sequential, and has as practical disadvantage that the computation time is longer than the pad printing cycle. Generating the scan itself is relatively fast, but the subsequent processing and correlation is slow. More problematic is that during the scanning analysis a number of errors accumulate, significantly decreasing the quality of the resulting probability distribution. The uncertainty originates from: 1. errors in generating the relevant part of the image, called searchbox; 2. errors in generating a significant curve in that searchbox under specific geometric and intensity constraints; and 3. errors in comparing these two scans using a reasoning algorithm that takes into account geometrical and chemical-physical padprinting expertise.

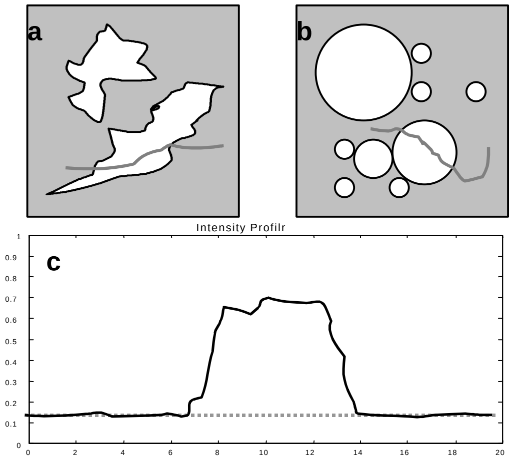

Fig. 4. a: Image with defect 'ink missing',
b: Image with defect 'air bubbles',
c: intensity profile compatible with a and b.

The largest deficit however is that in restricting the analysis to one-dimensional sets, unwanted ambiguity is introduced, as much of the original two-dimensional information is lost. Figure 4 shows one example where the restriction to 1D information causes difficulty to distinguish between two distinct defect classes.

3. A Direct 2D-Image Analysis Approach

The discontentment with the 1D scanning approach compared with the high human visual performance inspired the design of a parallel (but sequential implemented) method that utilises the entire 2D information. The logical choice for such an approach is a Neural Network (NN). Therefore, a simple three-layer feed-forward backpropagation network was designed and trained to perform padprinting-defect classification. In order to apply a NN on this task, however, a number of typical NN development problems must be addressed.

1.The design problem

The size of a whole CCD-image is typically 10^5 – 10^6 pixels, and as such impracticably large as inputspace for a NN. Moreover, in order to be practically applicable the approach should be template-invariant. Therefore, only small images are suitable as input. These images must represent characteristic parts of the entire image and must be large enough to indicate the defect class, but small enough in order not to contain any specific information of the template. In the course of the 1D scanning approach discussed above, searchboxes, i.e. patches of the image, are automatically generated on locations of the largest dissension between image and its template. The searchbox-algorithm was tuned in such a way that it generated patches of 16x16 pixels. In order to compare the observed patch with the template, an identical square with the coordinates of the searchbox was placed on the template, and its contents as an image of 16x16 pixels formed the second set for the input-space, see figure 5. The input of the NN therefore consisted of $2x2^4x2^4 = 2^9$ inputs – for each pixel one input. Each pixel can have 2^8 possible greyscale values. The best results were obtained with a hidden layer consisting of 20 neurons [3]. The output layer consisted of 5 neurons, each representing a specific padprinting defect for which the system would be trained.

2. The training problem

Due to the large size of the network a large trainingset was necessary. The training of the Network was limited to 5 defect classes. A collection of 260 CCD-images containing

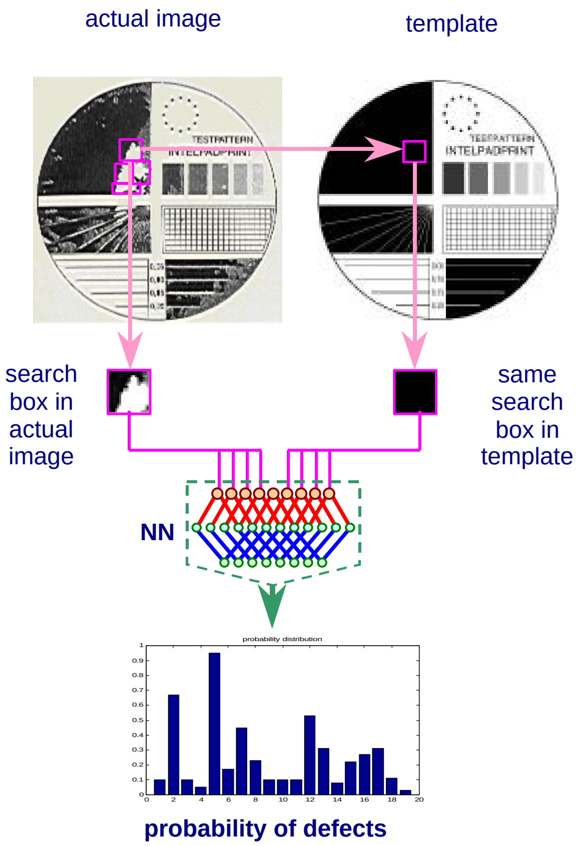

Fig. 5. A neural network is trained to compare a 16x16 searchbox automatically generated on a relevant spot on an defect image with the same searchbox on the template. In controlled experiments the approach works satisfactory.

those 5 defects was available. The searchbox-algorithm automatically generated relevant patches on the image of 16x16 pixels. In this way, each image generated large numbers of patches. This led to a trainingset of more than 25K examples. The testset contained another set of 76 examples. While the design and realization of this approach was extremely straightforward and fast, once more demonstrating the power of neural nets, the training of the network, however, clearly indicated one of the major drawbacks of neural nets; the long training times and the lack of convergence. Because of the black-box character of NNs, it was not clear whether back-propagation had guided the system to a local or a global optimum. The result could be improved by altering the design of the network or changing some of the many design and training parameters. This complexity constitutes another well-known disadvantage of neural nets. Though after some of such adjustments the performance of the system reached a satisfactory 80%, it was not able to surpass the performance of the scan approach, see figure 9.

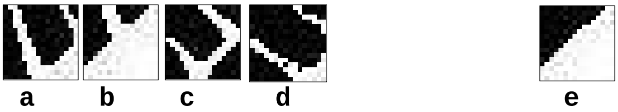

Fig. 6. Some examples of 16x16 searchboxes on identical spot in different test-images. (**a-d**): test-images with a defect called 'hairs', (**e**): searchbox on identical spot in the adequate template.

4. Fuzzy Interpretation of the NN Output

Rather than a probability distribution over the defect classes, the output is regarded as a fuzzy measure $m_k(\boldsymbol{x})$ that represents the correspondence of inputvector $\boldsymbol{x}$ to defect class k, or alternatively the membership of the outputvector to defect class k. The fuzzy interpretation of the NN is called the *NeuroFuzzy System* (NFS). This is a more genuine representation of the real situation where most defects are not sharply separated, but gradual transitions exist between certain defect-classes. All defects are clustered within six clusters with similar physical-chemical or mechanical causes.

5. Clustering of Defects

Two clustering techniques were engaged to find relevant clusters in the outputspace, Fuzzy C-means (FCM) and Kohonen Self Organising Feature Map (SOFM). Both techniques succeeded well in identifying relevant clusters, with almost identical results. In most cases FCM generated better clusters and prototypes, and the advantage of SOFM was its planar representation of the clusters. Using the NFS and the SOFM-clustering, a simple mathematical model demonstrates how printing defects are distributed in the output space. The model is confined to two printing defects; *'Double Print'*, and *'Misregistration'*, see figure 7. A parameter λ represents the 'strength of the defect'. In this case NFS can be used to 'compute' $\mu_K(\mathbf{x}(\lambda))$ as function of λ, and so obtain the 'trajectory' of the defects in the output space. Employing the SOFM-clustering, the corresponding trajectories of the defects on the 2D-Kohonen map are determined. Figure 8 depicts the results, showing that the two defects do not overlap. Thus, the Kohonen-map can be divided in three exclusive parts: a. an area where 'double print' can occur, b. an area where 'misregistration' can occur, and c. an area where neither (a) nor (b) can occur. Generalising this idea the Kohonen-map can be used to classify actual printing-images, at least to their correct cluster.

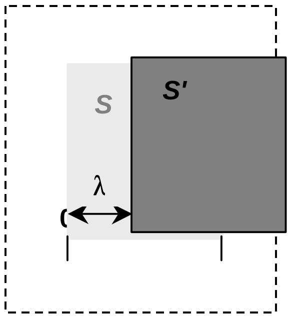

Fig. 7. A square *S* is translated by an amount 'λ', the dashed square is the frame observed by the camera. This is a simple model for the defects 'misregistration' (only S' printed), and 'double print' (S and S' printed).

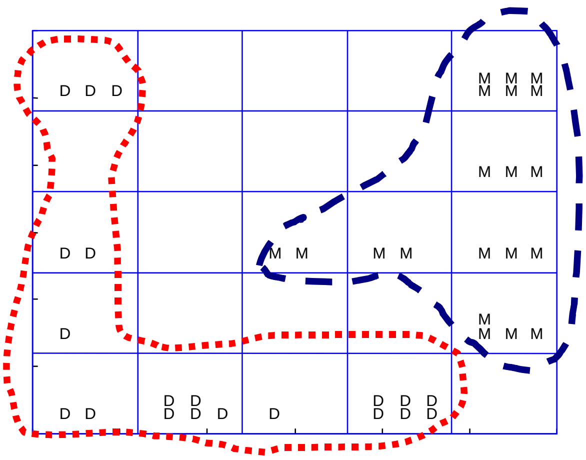

Fig. 8. Kohonen-representation of the trajectories of defects 'misprint' (M) and 'double print' (D).

6. Experimental Results and Conclusions

Our objective was to study the applicability of a NeuroFuzzy System to process the full 2D information of (part of) a CCD-image, and its ability to correctly identify the padprinting defect. A system was developed and trained on a limited set of 5 defects. The results indicate that for this set the method is indeed able to identify the defect class with an average performance of 80%, see figure 9. The results from paragraph 5 indicate that the cluster to which a defect belongs can be identified with an even higher performance. A second objective was the comparison of this approach with conventional 1D scanning methods. Our results show that in general the performance is comparable, but the NeuroFuzzy approach is more dependent on the template than the 1D-scanning approach. On the other hand, the NFS is able to recognise certain defects that the 1D-scanning approach cannot identify without employing extra tools, for instance 'air bubbles' (nr. 2 in fig. 9) and 'ink missing' (nr. 5 in fig. 9).

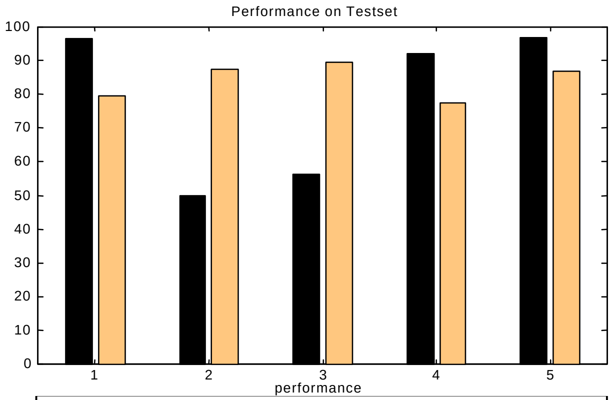

Fig. 9. Performance of the NFS on a testset of defects. On the horizontal axis the defect-nr and vertically the performance. Black = 1D scanning, grey = NSF

The design and realization of the NFS approach was extremely straightforward and fast, compared with the design and development of a 1D-scanning approach, once more demonstrating the power of neural nets. On the other hand however, the training of the neural network clearly indicated one of the major drawbacks of neural nets; the long training times and the lack of convergence.

Finally, the ability to adapt is shared by both approaches. The scanning is based on statistical correlations between scans and defects, and as such can 'improve' its performance as more examples are offered to the system. This however, contrasts sharply with the ability of the NFS to generalise and associate, as it is more 'trained' in time.

Though more research is necessary the conclusion is that the neural network offers additional information to the LCA-Diag method. Though larger training sets and longer training times should theoretically lead to a better performance, the approach was not implemented in the test system. The reason was the unpredictability of the NFS system for new input because of the black-box character. In the end the design is based on a perhaps potentially inferior but more predictable performance.

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